2 RELATIVE SIGNED JUMP AND FUTURE STOCK RETURNS

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Abstract

Due to the importance of expected return on investment documented in financial literature, studies have developed and examined numerous methods and techniques and assessed their predictability power. This research examines if realized variation measures of individual firms contain information for future stock returns using trading strategy that takes long position for portfolio of stocks having high realized variation measures and takes short position for portfolio of stocks having low realized variation measures. Relying on recent advancements in asset pricing, intraday stock price increments are decomposed into their positive and negative constituents and their summed squares are categorized as good and bad volatilities, respectively. On the basis of the findings, it is evidenced that relative signed jump measure (RSJ) acquired by taking the difference of good and bad volatilities, scaled by total daily volatility, has positive risk premium in the cross section of stock returns in the emerging stock market of Pakistan. Results for realized kurtosis (RKT) are also positive and significant for predicting next week's cross sectional stock return. Furthermore, the predictive power of realized volatility (RVOL) and realized skewness (RSK) are analyzed, but no robust evidence is traced for these realized measures.

Keywords: cross-section of equity returns, emerging market, intraday data, realized skewness, relative signed jump

JEL classification: G10, G12, G17, O16

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1. Introduction

Examining Stock return predictability is broadly regarded as a stylized fact: time varying property of expected returns is indicated by theory and supported by numerous studies. For example, Lettau and Ludvigson (2001) document the widely acceptable variables such as dividend price ratio, earnings price ratio, dividend earnings ratio and a cluster of other economic indicators in the predictability of excess stock returns. Ang *et al.* (2006) and Farago and Tedongap (2018) argue that the conventional linear risk return tradeoff is oversimplified and that precise return forecasts in the cross section, could be acquired by decomposing volatility into upside and downside constituents. Other studies have tried to formulate numerous pricing kernels for compensating investors to bear the risk due to higher market moments (Kraus and Litzenberger, 1976; Harvey and Siddiqui, 2000; Ang *et al.,* 2006; Chang *et al.,* 2013). Intuitively, stocks having higher downside risk have high expected returns. Starting from Roy (1952), researchers recognize that investors put different weight on downside risk as compared to upside uncertainty. Markowitz (1959) supports the use of semi variance to replace variance in measuring risk due to its capacity to deal with upward and downward movements differently. Kahneman and Tversky (1979) provide behavioral configuration of risk averse preferences. Similarly, the axiomatic technique of Gul (1991) define disappointment averse behavior that permit agents to care greater about downside losses than upside gains in their utility framework. Thus, agents require higher premium for their exposure to downside risk in their future returns and are willing to discount for upside gains (Ang *et al.,* 2006).

Bollerslev *et al.* (2020) use relative signed jump (RSJ) and compares it with realized volatility (RVOL), realized skewness (RSK) and realized kurtosis (RKT) measures to predict one week ahead stock returns. They find a negative relation between RSJ and subsequent week's stock returns using sample of 19,896 firms for the period from January 4, 1993 to December 31, 2013 in the stock market of United States. However, evidence of our study is different from the literature on advanced economies (e.g., Bollerslev *et al.,* 2020) in several ways. First, this study finds that weekly average relative signed jump (RSJ) and realized skewness (RSK) are positively priced (investors are compensated with positive risk premium for their exposure to RSJ and RSK risk) in the cross section of stock returns for 306 firms listed at Pakistan Stock Exchange (PSX). The sample used for analysis is accompanied by high-impact information releases. High-impact information releases such as earnings announcements cause extremely large price increments, termed as jumps in asset prices (Choi and Lee, 2014). A large number of researches suggest the importance of information releases on the expected stock returns (e.g., Pritamani and Singal, 2001; Chan, 2003; Tetlock, 2010; Savor, 2012). These studies argue that stock returns show momentum if price increments are accompanied by information releases as investors under react in this scenario, while stock returns show return reversal when price increments are not accompanied by information as they overreact to other shocks. The results for RSK measure in this paper are consistent with Choi and Lee (2014). However, the predictability power of RSK is completely reversed after controlling for the RSJ measure, documenting that RSK is not a robust measure to predict cross section of equity returns. Secondly, the results for long short returns on quintile portfolios comprising stocks ranked on lagged realized kurtosis (RKT) are statistically significant. Iqbal *et al.* (2010) find the usefulness of excess kurtosis to explain Pakistan stock market returns over and above Fama and French three factor model. In the emerging economies, infrequent trading for most stocks results in excessive zero returns leading to large kurtosis. However, no evidence is observed for the realized volatility (RVOL) measure. Finally, in contrast to Bollerslev *et al.* (2020), who report that the positive jump is 38% higher than the negative jump for a RSJ value of 1 standard deviation away from 0, this research finds a 66.64% higher value for the same, depicting extreme volatility episodes at the emerging stock market of Pakistan.

This study contributes to the literature by finding a robust positive relationship (different from the results in developed economies, e.g., Mizrach *et al.,* 2018; Bollerslev *et al.,* 2020) between RSJ and future returns depicting the higher potential to earn abnormal returns at Pakistan Stock Exchange (PSX). According to Iqbal (2012), investors are compensated with enormous profits for their exposure to higher volatility at PSX caused by noisy market makers and speculators. Thus, the non-normality of asset returns is an outcome of the jump part of variation and as stock returns of emerging markets tend to be non-normal, incorporating the RSJ measure is more appropriate for risk-return analysis.

The organization of the remaining paper is as follows. Section 2 discusses the existing literature, Section 3 presents the data and methodology, Section 4 deals with data analysis and findings and Section 5 concludes the study.

2. Literature Review

Measuring volatility and understanding its dynamics play a crucial role in dealing with many fundamental issues in the field of finance. The presence of multiple competing techniques for measuring volatility calls for more suitable measures. One such approach relying, for example, on the squares of returns over the suitable return horizon offers unbiased and highly efficient estimation of ex-post realized volatility (Karatzas and Shreve, 1991). According to Andersen et al. (2001), taking square of returns is also a noisy measure of volatility and thus does not permit to infer reliably about the true underlying latent volatility. Andersen et al. (2003) advance by putting focus on empirical computation of daily return variance known as realized volatility, which is smoothly calculated from high frequency intraday returns. As suggested by the theory of quadratic variation, under appropriate preconditions, realized volatility is a robust estimator of stock return volatility. Theoretically, the increase in data frequency, for example, from daily to infinitely short time period, leads to genuinely measuring the latent volatility component. Practically, however, it shows infeasibility due to sample limitations and the existence of market microstructure noises containing non-synchronous trading consequences, discretization, intraday periodical volatility patterns, bid ask spread jumps, etc. Andersen and Bollerslev (1998) find that their suggested volatility estimates using high frequency data reduces noise dramatically and radically improves temporal stability as compared to techniques using daily data. Furthermore, daily volatility approaches are found to function well when compared against these enhanced volatility estimates because of their explanatory power for almost half of the variance in the volatility constituent. Particularly, building on the time varying stochastic volatility model provided by Nelson (1990), Andersen and Bollerslev (1998) depict the ability of high frequency data in constructing broadly enhanced estimates of ex post volatility through sum of squares of intraday returns.

The use of variance as a measure of portfolio risk has not always been satisfying to financial theorists. Markowitz (1959) proposes semi-variance as an alternative risk measure in his pioneering paper on portfolio selection. Application of semi-variance and broader category of downside risk techniques is analyzed by many studies in finance (e.g., Hogan and Warren, 1974; Lewis, 1990; Ang et al., 2006). Downside variance measure is considered as a more suitable approach to determine risk than total volatility of stock returns. Patton and Sheppard (2015) show that volatility of intraday negative stock returns carries information to predict future volatility by taking data on firms in S&P 500 and S&P 100 for the period from 1997 to 2008. They find that the negative and positive signed constituents of realized volatility have higher explanatory power for extended horizons as compared to an estimator that is not distinguishable based on sign; however, their role is asymmetric (bad or downside volatility predicts higher long term variation and good or upside volatility predicts lower long term variation). Downside risk is related to the risk of assets when economic conditions are adverse and upside uncertainty happens in a promising economic environment. The existing literature (e.g., Farago and Tedongap, 2018) treats the two risks asymmetrically and has developed new techniques for computing cost of capital and managing risk such as value at risk and expected shortfall. Theorists provide frameworks for rational behavior of investors where they put higher weights on downside risk. The lower partial moment function (Bawa and Lindenberg, 1977), the prospect theory addressing loss averse behavior of investors by Kahneman and Tversky (1979) and the axiomatic approach of Gul (1991) related to disappointment aversion which was later amended by Routledge and Zin (2010) are among the few.

Similar to standard realized volatility measure described by Andersen et al. (2001) as sum of squares of high frequency intraday price increments, the apropos upside and downside realized volatility components are simply computed by summing squares of positive and negative intraday returns respectively (e.g., Barndorff-Nielsen et al., 2010). According to Bollerslev et al. (2020) the variation because of continuous processes is similar for upward and downward realized semi-variances; therefore, their difference is a manifestation of variation caused by jumps. Barndorff-Nielsen et al.'s (2010) theoretical framework demonstrates that subtracting downside realized volatility from its upside constituent eliminates the variation due to continuous process. This difference removes the common integrated variation in both terms and provides a positive measure when upward jump dominates the day and a negative measure when downward jump dominates the day (Patton and Sheppard, 2015). A recent study of Bollerslev et al. (2020) focuses on the firm level relative difference of the up and down realized semi-variance measures rather than considering them individually and show the role of relative signed jump in strongly predicting the future stock returns in the cross section. The basic instinct supporting this technique relies on the economic rationale that the investor not only requires risk premium to accept potential downside losses, but is also ready to forego returns for potential upward gains (Breckenfelder and Tedongap, 2012).

Similar to realized volatility, realized semi-variance convenes to half of the integrated volatility function in addition to variation stemming from signed jump using high frequency data. Signed jump estimator is constructed to capture the variation in stock price increments caused by jump component only, by removing the variation resulting from continuous process (Patton and Sheppard, 2015). Amaya et al.'s (2015) estimator, realized skewness shows similar convergence of the jumps in stock returns took up to a binomial third degree scaled by realized variance. RSJ offers a simpler to compute and analyze variation measure, plainly instigated by the intuition that assets having different degree of good versus bad volatility manifested by signed jump measure may be valued in a different way in the cross section.

The role of realized moments in dealing with the time varying nature of stock returns is specifically important. The forecasting power of these estimators based on high frequency data was shown by many studies (e.g., Fleming et al., 2003; Andersen et al., 2003; Andersen et al., 2007). Andersen et al.'s (2007) study stands out by using non parametric measurements for decomposition of quadratic variation into a constituent due to continuous process and a jump component to gain insights into the dynamics of total volatility and to explore level of persistence of both the constituents and how these interact with each other. Realized estimators are also used to evaluate volatility forecasting by research (e.g., Andersen et al., 2005; Patton, 2011).

Thus, set against this background, this study conducted taking intraday data of PSX from July, 2008 to August, 2018, provides fresh insight regarding stock return predictability using high frequency data in an emerging market. The results of this research may enhance the decision-making ability of investors to ensure maximum returns at PSX. To the best of authors' knowledge, this is the second research conducted at PSX (first conducted by the authors, Rehman et al., 2021 in a different vein) to analyze if realized measures are helpful in describing stock returns, computed using intraday data; therefore, the devised research methodology generates more refined analysis and findings which provide accurate and thorough information of asset pricing at PSX.

3. Data and Methodology

3.1. Data

The intra-day stock price data for 306 listed firms meeting the selection criteria for the time period between July 1, 2008 and August 31, 2018 are obtained from Pakistan Stock Exchange to compute returns of five minutes intervals. Andersen et al. (2001) suggests that using five minutes interval sample, removes the effects of measurement error and micro structure noises from realized measures. Following conventional approach (e.g., Choi and Lee, 2014; Bollerslev et al., 2020) nearest neighbor method is used to interpolate 5 minutes prices based on tick by tick data for trading hours from 9:30am to 3:30pm (Monday to Thursday) and from 9:15am till 4:30pm for Fridays, such as there are 72 observations with 5-minute prices for Monday till Thursday and 57 for Fridays, which translates into weekly realized variation measures from 345 observations for each firm. Stocks that have prices of Rs. 5 and more (to avoid getting large returns) and at least 80 trades / transactions during a trading day are considered for analysis. Based on the now long standing concept of realized volatility (which is computed by summing intraday squared returns), realized skewness and kurtosis are acquired by using intraday cubed and quartic returns as in Amaya et al. (2015). To compute control variables, daily data of closing prices, trading volume and market capitalization are also acquired from the Pakistan Stock Exchange. Six months T-bill rate is used to proxy for risk free rate and KSE 100 index for market risk. Firm level five minutes returns are used to calculate realized measures of RSJ, RVOL, RSK and RKT, daily returns are used to compute market beta, momentum variable, lagged return, idiosyncratic volatility, maximum and minimum return within the prior week and illiquidity (Amihud, 2002).

Monthly closing prices are used to compute co-skewness (Harvey and Siddique, 2000) and co-kurtosis. This study obtained firm-level data of book value from Thomson Reuters Data-stream to calculate the book to market ratios.

3.2. Modelling Realized Variation Measures

3.2.1. Theory

The theoretical framework underlying realized moments and semi variance estimators depends upon the generality of high frequency asset returns over a fixed time interval. If PT presents logarithm of an arbitrary asset price, the basic assumption is that it follows a jump diffusion process.

$$PT = \int_0^T \mu_T d_T + \int_0^T \sigma_T dW_T + J_T \tag{1}$$

where: μ and σ are the drift and diffusive variation functions, respectively, W presents the regular Brownian motion and J the pure jump course. The unit time interval T relates to a trading day. The underlying assumption is intraday prices are recorded at an equal space during a trading day. Thus, the stock return at an *i*th time interval for a trading day *t+1* is denoted by:

$$r_{t+i/n} = P_{t+i/n} - P_{t+(i-1)/n} \tag{2}$$

The daily realized volatility is calculated by summing the squares of these intraday returns.

$$RV_t = \sum_{i=1}^{n} r_{t-1+i/n}^2 \tag{3}$$

By the framework provided by the existing literature, such as Andersen *et al.* (2001) and Andersen *et al.* (2003), the realized volatility convenes (for n → ∞) to the quadratic variation, which in part includes variance because of continuous process and variance because of jump constituent.

$$RV_t \to \int_{t-1}^{t} \sigma_s^2 \, ds + \sum_{t-1 \le T \le t} J_T^2 \tag{4}$$

Therefore, providing precise *ex post* estimates of the volatility of price increments using high frequency intraday returns.

The realized volatility estimator in equation (3) provides total variation; however, Barndorff-Nielsen *et al.* (2010) introduce downside and upside semi variance estimators acquired by decomposing realized volatility related to finer sampled positive and negative returns.

$$RV_t^+ = \sum_{i=1}^{n} r_{t-1+i/n}^2 \mathbf{1}_{\{r_{t-1+i/n>0}\}}, \qquad RV_t^- = \sum_{i=1}^{n} r_{t-1+i/n}^2 \mathbf{1}_{\{r_{t-1+i/n<0}\}}. \tag{5}$$

The sum of the both semi variance measures is apparently equal to the total realized volatility. Furthermore, it can also be shown that:

$$RV_t^+ \to \frac{1}{2}\int_{t-1}^{t} \sigma_s^2 \, ds + \sum_{t-1 \le T \le t} J_T^2 1(J_T > 0), \tag{6}$$

$$RV_t^- \to \frac{1}{2}\int_{t-1}^{t} \sigma_s^2 \, ds + \sum_{t-1 \le T \le t} J_T^2 1(J_T < 0). \tag{7}$$

The separated positive and negative partial volatility components convene to half of the integrated variation plus aggregated squares of jumps either positive or negative.

The above-mentioned limiting properties of semi variances show that their difference clears the variation caused by continuous constituent and, therefore, only presents variation due to jumps. This good minus bad realized variance estimator is referred to as the signed jump (SJ) variation.

$$SJ_t = RV_t^+ - RV_t^- \to \sum_{t-1 \le T \le t} J_T^2 1(J_T > 0) - J_T^2 1(J_T < 0) \qquad (8)$$

The degree of variation is different for different stocks. This may cause the signed jump measure having extremely high/low values for some stocks in the cross section due to their total volatility having extremely high/low values. Bollerslev *et al.* (2020) circumvent this issue by normalizing the signed jump measure with total realized volatility, termed as relative signed jump (RSJ).

$$RSJ_t = \frac{SJ_t}{RV_t} \qquad (9)$$

This restricts the RSJ values to lie between 1 and -1.

Additionally, following Amaya *et al.* (2015), related realized measures are also calculated like daily realized skewness:

$$RSK_t = \frac{\sqrt{n}\sum_{i=1}^{n} r_{t-1+i/n}^3}{RV_t^{3/2}} \qquad (10)$$

and daily realized kurtosis,

$$RKT_t = \frac{n\sum_{i=1}^{n} r_{t-1+i/n}^4}{RV_t^2} \qquad (11)$$

Similar to RSJ estimator, RSK and RKT have limiting properties (for n → ∞) manifesting variance resulting from jumps. However, RSK and RKT convene to within day jumps in stock returns took up to a binomial third and fourth degree, respectively, scaled by realized variance and therefore do not present directly analyzable forms of the standard skewness and kurtosis estimators.

Following, Amaya *et al.* (2015), this study analyzes stock pricing in the cross section using data of weekly frequency, daily realized measures are averaged over the week to obtain their weekly values. Thus the weekly realized volatility is computed as:

$$RVol_t = \left(\frac{252}{5}\sum_{i=0}^{4} RV_{T-i}\right)^{1/2} \qquad (12)$$

It could be noticed that the realized volatility measure is annualized as is standard to facilitate the evaluation of findings. Weekly values of RSJ, RSK and RKT estimators are calculated as:

$$RM^{Week} = \frac{1}{5}\sum_{i=0}^{4} RM_{T-i}, \qquad (13)$$

where: *RM* (realized measure) stands for RSJ, RSK or RKT estimators.

3.2.2. Construction of Portfolios

Quintile portfolios are formed, ranked on RSJ, RVOL, RSK and RKT. Equal weighted characteristics of these portfolios are reported for the same week and this process is repeated every week from July 2008 through August 2018. Portfolio characteristics are also calculated for other well-known determinants of equity returns including market beta, logarithmic values of market capitalization, BE/ME (Fama and French, 1993), momentum (Jegadeesh and Titman, 1993), lagged return (Lehmann, 1990), idiosyncratic volatility (Ang *et al.,* 2006), co-skewness (Harvey and Siddique, 2000), co-kurtosis, maximum weekly return, minimum weekly return (Bali *et al.,* 2011) and illiquidity (Amihud, 2002) to check if firm level realized variation measures are informative for cross sectional stock returns. Next, value and equal weighted quintile portfolios are formed by ranking stocks on their lagged realized variation measures to analyze if last week's RSJ, RVOL, RSK and RKT are helpful to predict stock returns of the subsequent week. The abnormal return from a zero-investment strategy that buys stocks in the highest quintile portfolio and sells stocks in the lowest quintile portfolio are calculated along with long short Carhart's (1997) alphas to analyze the linkages between realized measures and stock returns.

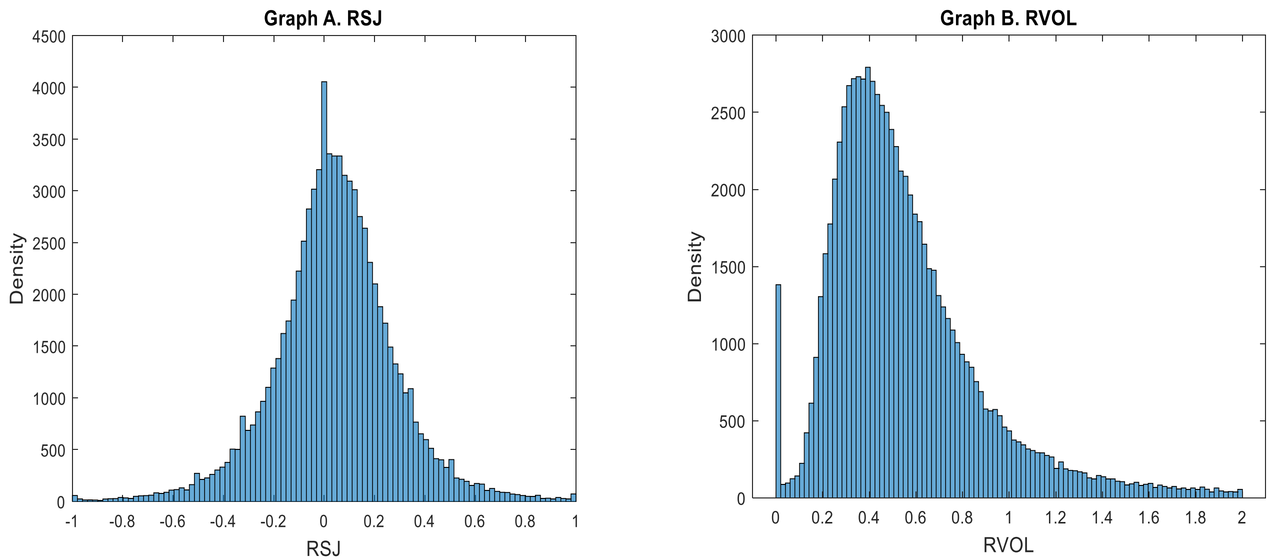
4. Data Analysis and Findings

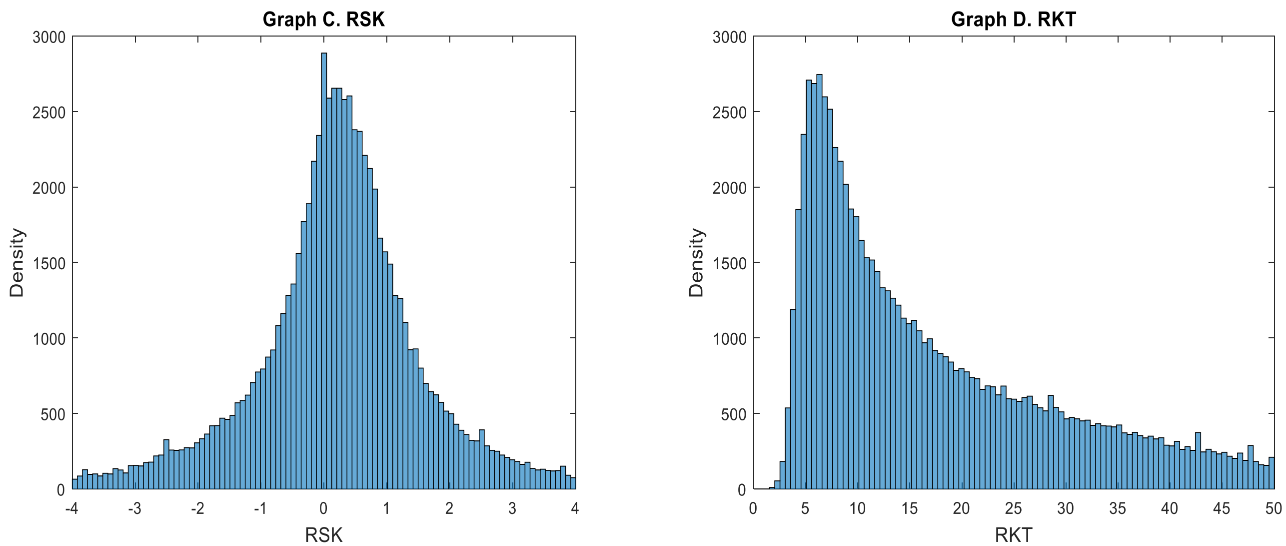
Unconditional distributions of realized estimators are shown in Figure 1 across sampled firms and weeks. As equation (8) above implies, Figure 1, Graph A of the RSJ estimator shows that the distribution is almost symmetrical around 0, depicting similar downside and upside jumps for individual firms, consistent with Chan *et al.* (2014) and Bollerslev and Todorov (2011) who find approximately symmetrical distributions for negative and positive jumps using high frequency data of market indices. The time series average of cross sectional standard deviation value of 0.25 of RSJ presented in Panel A of Table 1[7] hints that for a firm level weekly RSJ value of 1 standard deviation above 0, the positive jump is 66.64% higher than the negative jump, computed using equation (9). Also if the RSJ has a value of 0.5, the positive jump is three times larger than a negative jump. Thus this depiction of considerable variation of RSJ estimator across firms and through time relates to strong forecasting power for stock returns in the cross section (Bollerslev *et al.,* 2020).

Panel A of Table 1 reports the time series cross sectional averages of the cross sectional means and standard deviations not only for RSJ, RVOL, RSK and RKT but also for other well-known determinants of equity returns used as controls in this study and Panel B provides the corresponding weekly cross sectional correlations among the variables. The highest correlation of 0.9 observed between the new RSJ estimator and RSK at 1% level of significance is not surprising, as the two express asymmetries in intraday stock return distributions though the empirical results later reported in the paper demonstrate that RSJ is a stronger and more robust measure to predict the subsequent week's asset return than RSK. Moreover, the two variables do not show significant correlation with any other variable in the study (e.g., Boudt *et al*., 2011).

[7] *Tables 1 and 2 available online at https://www.ipe.ro/rjef.htm.*

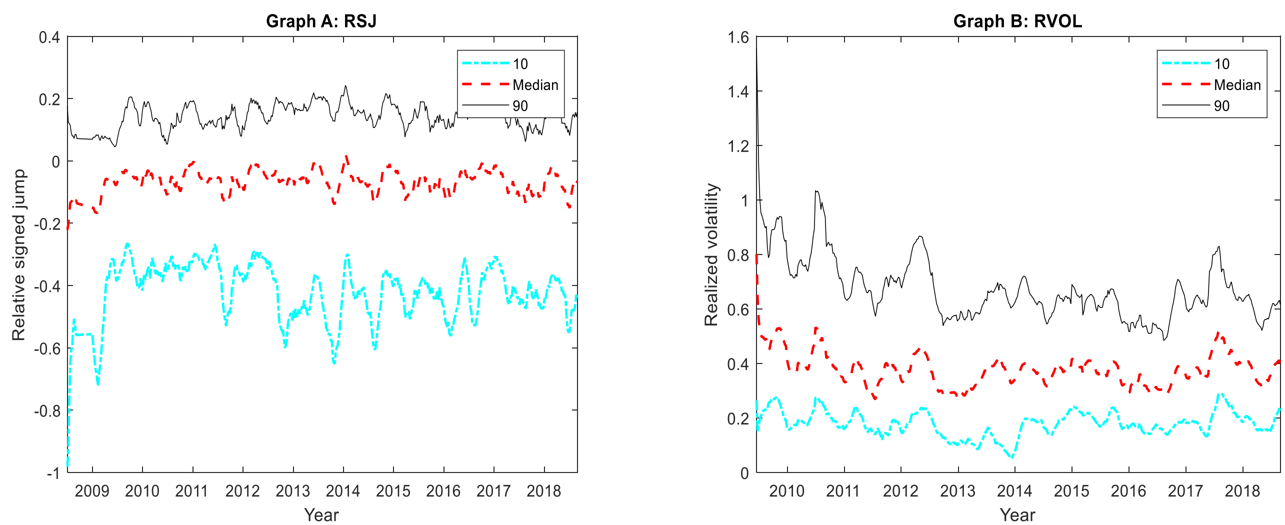
Figure 1. The Kernel Density Estimates of the Unconditional Distributions of the RSJ, RVOL, RSK, and RKT Realized Measures, Respectively, Averaged across All Firms and Weeks in the Sample

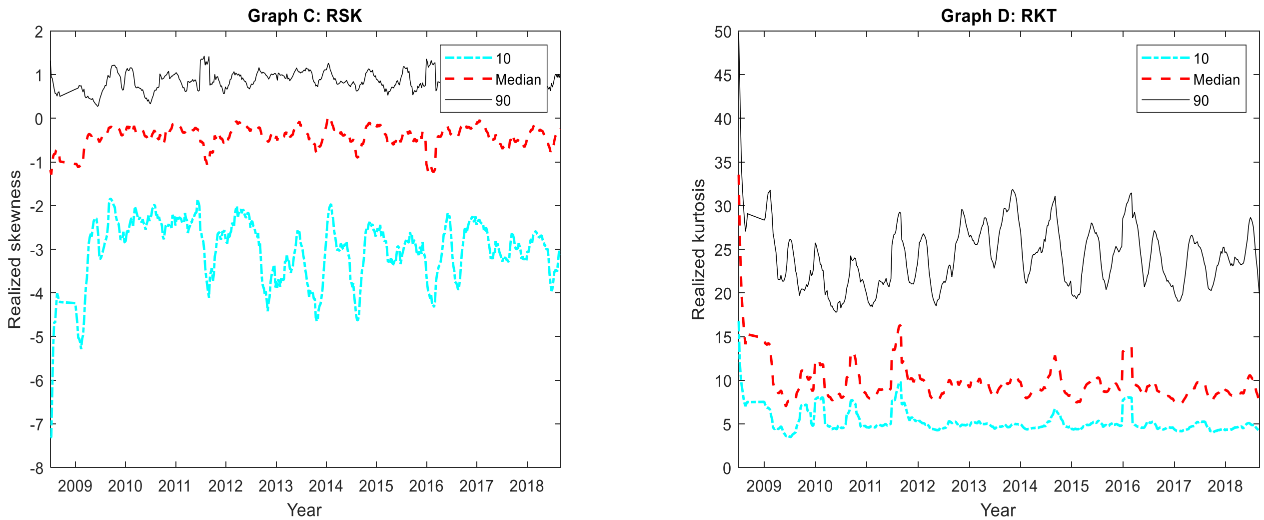




Note: Graphs B, C and D show that the shapes of unconditional distributions of RVOL, RSK and RKT are similar to Amaya et al. *(2015). Graph C of RSK though heavily tailed, has the same symmetrical distribution as Graph A of RSJ. Graphs B and D show rightly skewed distributions for RVOL and RKT, respectively. To elucidate the time variations implied by unconditional distributions of RSJ, RVOL, RSK and RKT, Figure 2 supports Figure 1 by plotting the 10 week moving means of different percentiles for the four realized variation measures.*

Figure 2. The 10-week Moving Average Time-series Percentiles of the RSJ, RVOL, RSK, and RKT Realized Measures, Respectively, Averaged Across All Firms in the Sample





Note: Graphs A and C of Figure 2 reveal stability in the cross-sectional percentiles of the RSJ and RSK measures; however, temporal variation is evident in the RVOL distributions depicted in Graph B with the marked peak in 2010 at all percentiles, attributed to the global financial crisis. The slight expansion in the RKT percentiles through time as observed in Graph D is consistent with previous evidence in literature, suggesting swelling fat tailed returns (e.g., Amaya et al.*, 2015; Bollerslev* et al.*, 2020).*

Time series means of different control variables sorted into equal weighted quintile portfolios based on their realized variation measures are presented in Table 2. The values of RSJ have increased from -0.303 in the first quintile to 0.37 in the fifth quantile as reported in Panel A of Table 2. Almost all control variables show patterns with RSJ, such as high RSJ firms are volatile firms having high RSK, MBETA, CSK and WMIN values (e.g., Bi and Cheng, 2014). Similar patterns could be observed for RSK in Panel C of Table 2, which is intuitive because of the high correlation between the two variables. However, high RVOL and RKT values are associated with small sized, less liquid firms having high BE/ME ratios as shown in Panel B and D of Table 2 respectively.

Next, the predictability power of all four realized variation measures is analyzed as displayed in Table 3. Panel A reports the weekly excess returns for quintile portfolios containing stocks ranked on RSJ. A positive relation is apparent between RSJ and next week's average returns as the raw returns for both value and equal weighted portfolios increase monotonically from low to high quintile, yielding a long short return of 1.42 with t-statistics of 10.54 on value weighted portfolio and a long short return of 1.71 with t-statistics of 16.75 for equal weighted portfolio.

Alphas from Carhart's (1997) four factor model are also analyzed to check if the return differences are an outcome of compensation for systematic risks. A similar strong positive link is evidenced between RSJ and abnormal equity returns as presented by Fama-French-Carhart 4-factor (FFC4) alphas. The alpha values for self-financed RSJ based strategy are 1.42 with t-statistics of 10.38 for value weighted portfolio and 1.7 with t-statistics of 15.76 for equal weighted portfolio. In contrast to Amaya *et al.* (2015) and Bollerslev *et al.* (2020), who find negative relation between RSK and subsequent week's stock return, this research finds a statistically significant positive relation between RSK and future returns as displayed in Panel C, such as investors are compensated with additional returns for taking skewness risk (e.g., Rehman *et al.,* 2021).

Choi and Lee (2014) evidenced a positive relation between RSK and weekly future returns for firms who provide information data publicly. The sample used in this study comprises of listed firms at PSX that are mandated to provide all the information on public forums; therefore, the results confirm the findings of Choi and Lee (2014). The average abnormal returns for zero investment strategy related to the predictability of RSK are 1.09 with t-statistics of 7.40 for value weighted portfolio and 1.36 with t-statistics of 14.08 for equal weighted portfolio. The results for RVOL in Panel B are insignificant but are exhibiting significant findings for RKT in Panel D for long short spreads. F values of GRS test further support the evidence.

The performance of the four realized variation measures is analyzed by plotting the long short portfolios' returns through time. Cumulative returns for each of the value and equally weighted strategies are displayed by Graphs A and B in Figure 3. The superior performance of RSJ long short strategy as compared to RSK is evident in both the graphs for value and equal weighted portfolios. The value weighted cumulative returns based on RVOL and RKT are almost flat throughout the sample period and go negative for RVOL for equal weighted strategy supporting the results of Table 3.

The findings in Table 3 show that RSJ and RSK are strong predictors for next-week returns. Following Bollerslev et al. (2020), a robustness test is conducted to further investigate their predictive power.

Table 3. Predictive Single-Sorted Portfolios

	Panel A: RSJ					**Panel B: RVOL**			
	Value Weighted		Equal Weighted			Value Weighted		Equal Weighted	
Quintile	Raw Return	FFC4	Raw Return	FFC4	Quintile	Raw Return	FFC4	Raw Return	FFC4
1 (Low)	-0.76	-0.86	-0.81	-0.9	1 (Low)	-0.18	-0.26	-0.03	-0.13
2	-0.33	-0.42	-0.41	-0.53	2	-0.03	-0.14	-0.05	-0.16
3	-0.15	-0.29	-0.16	-0.29	3	0.01	-0.12	-0.1	-0.23
4	0.07	-0.02	0.03	-0.09	4	0.05	-0.06	0.01	-0.12
5 (High)	0.66	0.56	0.9	0.8	5 (High)	0.04	-0.08	-0.16	-0.26
High-Low	1.42	1.42	1.71	1.7	High-Low	0.22	0.18	-0.13	-0.13
	(10.54)	(10.38)	(16.75)	(15.76)		(1.09)	(0.91)	(-0.99)	(-1)
FGRS		49.4504		88.8329	FGRS		1.5686		1.0012
p-value		(0)		(0)	p-value		(0.1542)		(0.4238)
	Panel C: RSK					**Panel D: RKT**			
	Value Weighted		Equal Weighted			Value Weighted		Equal Weighted	
Quintile	Raw Return	FFC4	Raw Return	FFC4	Quintile	Raw Return	FFC4	Raw Return	FFC4
1 (Low)	-0.65	-0.75	-0.61	-0.70	1 (Low)	-0.06	-0.17	-0.25	-0.39
2	-0.42	-0.53	-0.40	-0.52	2	-0.08	-0.2	-0.15	-0.3
3	0.02	-0.10	-0.11	-0.25	3	-0.03	-0.13	-0.15	-0.27
4	0.04	-0.05	-0.02	-0.13	4	0.14	0.06	0.03	-0.06
5 (High)	0.43	0.33	0.76	0.65	5 (High)	0.21	0.15	0.14	0.07
High-Low	1.09	1.08	1.36	1.35	High-Low	0.27	0.32	0.39	0.46
	(7.40)	(7.83)	(14.08)	(13.15)		(1.83)	(2.33)	(3.09)	(3.7)
FGRS		15.2661		33.9961	FGRS		1.3931		2.7213
p-value		(0)		(0)	p-value		(0.2154)		(0.0131)

Note: Table 3 reports the average returns for the predictive single-sorted portfolios. At the end of each week, stocks are sorted into quintiles according to realized measures computed from previous week high-frequency returns. Each portfolio is held for 1 week. The column labeled "Raw Return" reports the average 1-week ahead excess returns of each portfolio. The column labeled "FFC4" reports the corresponding Fama - French - Carhart 4-factor alpha for each portfolio. The row labeled "High-Low" reports the difference in returns between portfolio 5 and portfolio 1, with t-statistics in parentheses. F-statistics of GRS test along with their p-values are also reported. RSJ, RVOL, RSK, and RKT denote the relative signed jump variation, realized volatility, realized skewness, and realized kurtosis, respectively. In each panel, the first 2 columns report the value-weighted sorting results and the last

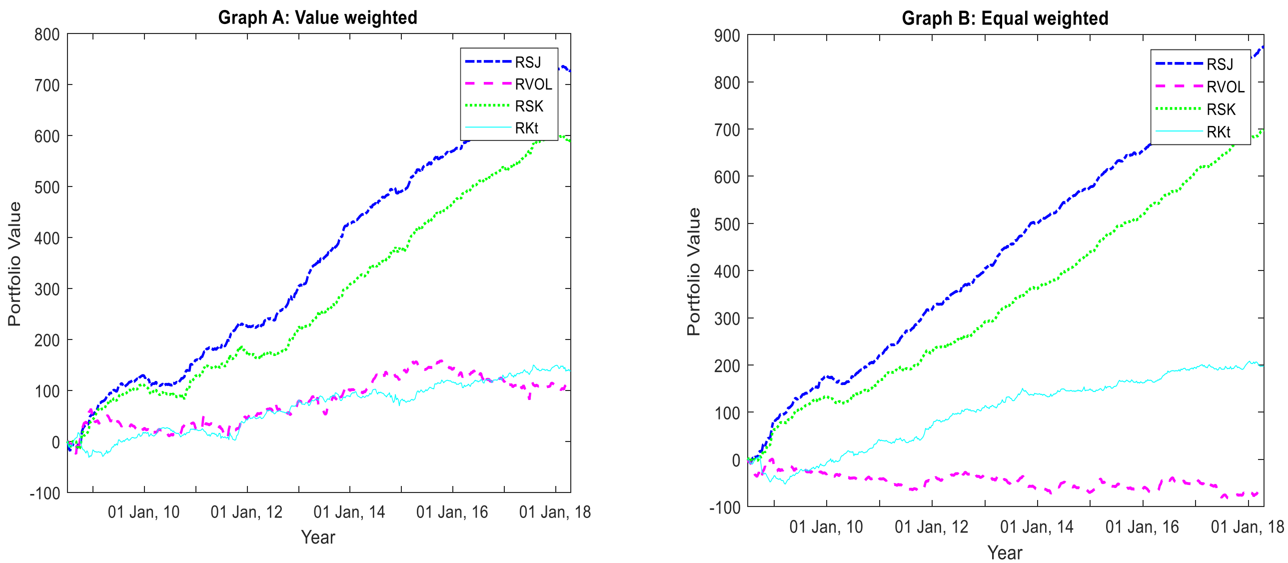
2 columns report the equal-weighted sorting results. Panel A displays the results sorted by RSJ, Panel B by RVOL, Panel C by RSK, and Panel D by RKT.

4.1. Robustness Analysis

A strong cross sectional relation between RSJ and RSK estimators is evidenced by the correlation coefficients and portfolio sorts presented in Tables 1 and 2. To capture the unique information content in these estimators, every week a cross-sectional regression of RSJ against RSK and RSK against RSJ is run and stocks are sorted on the basis of regression residuals. Panel A of Table 4 reports the raw returns and Carhart's (1997) alphas of quintile portfolios based on RSJ residuals orthogonal to RSK. The long short spreads are highly significant for both value and equal weighted portfolios. On the other hand, the results are completely reversed for RSK residuals orthogonal to RSJ as compared to RSK rankings in Panel C of Table 3 producing positive return predictability. Instead, RSK residuals negatively predict the next week's stock returns as shown in both the FFC4 columns in Panel B. For example, the long short value weighted FFC4 alpha of -0.77 with a t-statistics of -6.19 is higher in magnitude and significance in statistical terms. If these findings were produced by measurement errors in RSK, that would result in diminished positive relation and not sign reversal. Instead, the findings imply that the high contemporaneous correlation and strong positive predictive power presented in Table 3 is attributable to the common constituent shared by RSJ and RSK. However, after controlling for this common constituent that manifests more firmly in the RSJ estimator, the predictability of RSK is entirely different.

To check if the results for RSJ are consistent across different sub samples, data is divided into two equal parts. The value and equal weighted weekly raw returns (in bps) of portfolios constructed on the basis of RSJ for the two sub samples are reported in Table 5. The results for long short returns based on realized RSJ are still positive and highly significant as shown in Table 5. Thus, the findings of this study assert that RSJ is a robust measure to predict the future stock returns. The results for RVOL are insignificant, but adequate evidence is found for the forecasting power of RKT. RSK fails to provide consistent results when it is purged from the influence of RSJ.

Figure 3. The Cumulative Gains



Note: Graph A of Figure 3 shows the cumulative gains for a value-weighted long-short portfolio based on RSJ, RVOL, RSK, or RKT. Graph B shows the cumulative gains for an equal-weighted long-short portfolio. All of the portfolios are re-balanced and accumulated on a weekly basis, as described in the main text in Section 3.2.2.

Table 4. Predictive Single-Sorted Portfolios with Controls

Panel A. Sorted by RSJ Residual Controlling for RSK					Panel B. Sorted by RSK Residual Controlling for RSJ				
	Value Weighted		Equal Weighted			Value Weighted		Equal Weighted	
Quintile	Raw Return	FFC4	Raw Return	FFC4	Quintile	Raw Return	FFC4	Raw Return	FFC4
1 (Low)	-0.49	-0.59	-0.51	-0.61	1 (Low)	0.45	0.34	0.31	0.21
2	-0.32	-0.42	-0.41	-0.52	2	0.05	-0.05	0.01	-0.1
3	-0.12	-0.22	-0.14	-0.25	3	-0.11	-0.22	-0.11	-0.24
4	0.1	-0.02	0.11	-0.02	4	-0.26	-0.37	-0.36	-0.49
5 (High)	0.53	0.41	0.56	0.45	5 (High)	-0.33	-0.43	-0.23	-0.33
High-Low	1.02	1	1.07	1.07	High-Low	-0.79	-0.77	-0.54	-0.54
	(8.34)	(8.47)	(11.41)	(11.15)		(-6.31)	(-6.19)	(-5.75)	(-5.22)
FGRS		10.6358		19.0760	FGRS		11.6509		14.4347
p-value		(0)		(0)	p-value		(0)		(0)

Note: Table 4 reports the average returns for predictive single-sorted portfolios with controls. At the end of each week, stocks are sorted into quintiles according to realized measures with controls computed from previous week high-frequency returns. Each portfolio is held for 1 week. The column labeled "Raw Return" reports the average1-week ahead excess returns of each portfolio. The column labeled "FFC4" reports the corresponding Fama-French-Carhart 4-factor alpha for each portfolio. The row labeled "High-Low" reports the difference in returns between portfolio 5 and portfolio 1, with t-statistics in parentheses. F-statistics of GRS test along with their p-values are also reported. RSJ and RSK denote the relative signed jump variation and realized skewness. In each panel, the first 2 columns report the value-weighted sorting results and the last 2 columns report the equal-weighted sorting results. Panel A displays the results sorted by RSJ residual controlling for RSK and Panel B by RSK residual controlling for RSJ.

5. Conclusion

The previous literature provides evidence that RSJ and RSK are negatively priced in the cross section of stock returns explained by the investors' skewness preference (e.g., Amaya *et al.* 2015; Bollerslev *et al.* 2020). However, some (e.g., Choi and Lee 2014) find opposite relation between RSK and future return, asserting that RSK captures information uncertainty related to firm's fundamentals. This research investigates the cross sectional characteristics of realized variation measures, relying on methodology used by Bollerslev *et al.* (2020). The findings exhibit that firms having relative high/low good minus bad variations formed by summing intraday positive and negative return squares respectively, have high/low subsequent week's returns. The return difference of the trading strategy that goes long on stocks in the top RSJ based quintile and goes short on stocks in the bottom RSJ based quintile is 1.42% per week with corresponding t-statistics of 10.54 for value weighted portfolios, exceeding the hurdle rate, Harvey *et al.* (2015) advocate, to judge the cross-sectional return predictability. The adjustment for conventional Carhart's (1997) systematic risk factors does not change this return difference and its robustness. The return differences for equal weighted RSJ portfolios are even larger in magnitude and statistical significance, whereas, there is a complete reversal of positive predictability of RSK after controlling for RSJ effect.

Evidence from this study shows that RSJ is a more robust measure for stock return predictability. Since the population mean of RVOL is independent of periodicity of underlying stock price increments, the population means of RSK and RKT varies with periodicity of sample used. Moreover, the two higher order moments, RSK and RKT are more susceptible to outliers in their calculation and difficult to provide precise estimates. Investors and portfolio managers can gain excess return by adopting RSJ based long short portfolio making strategy. There are several areas that can be explored using intraday data in the emerging stock market of Pakistan. In this research, the role of realized variation measures is analyzed for predicting cross-sectional stock returns. However, future researches can check if these realized measures are useful to forecast time series of stock returns. The role of realized measures to predict the stock market volatility could also be checked in future studies.

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